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Analyzing the Impact of Social Media Sentiments on Government Response During Natural Disasters in Pakistan

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Abstract

In light of the growing frequency of natural disasters, social networking sites are now used for polling perception and evaluating governmental performance. This study aims to examine the effects of negative and positive social media discussions on government responses to the flood disaster of 2010 in Pakistan. This study, being a sentiment analysis of tweets that involve the Pakistan Flood 2010 and Disaster Relief hashtags only, classified public responses as positive, negative, or neutral. The sentiments are transformed into actionable insights using the Enhanced Hybrid Dark Social Analytical Framework (EHDSAF) technique across different areas. The study advances knowledge of how public sentiment shapes government responses by showing that negativity correlates with slower responses and revised policies. The majority of the tweets analyzed were neutral (45%), followed by positive (35%) and negative (20%). Negative sentiment tends to be concentrated during the peak crisis period. Higher negative sentiment, particularly in big cities correlates with more immediate and substantial government interventions, indicated by a strong correlation of 0.65. The Pearson correlation coefficient calculated as 0.68, suggests a strong relationship between public sentiment and response. The study, therefore, establishes social media as an accountability forum that provides real-time feedback to government agencies in the course of calamity management. This paper highlights the effectiveness of using sentiment analysis to update the approach by which disasters are responded to, as well as improve the perception of the public towards government endeavors.

Keywords: EHDSAF, Twitter, Dark social data, API, Sentiment analysis, GOP, Machine learning, VADER.

1 | Introduction

Natural disasters, in most cases, result in the loss of property and also affect people socially, economically, and emotionally [1]. Crisis communication mostly takes place on social media, especially on such specific platforms as Twitter, Facebook, or Instagram. In the 2010 flood in Pakistan [2], social media was reportedly

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useful in the spreading of information about the flood, sharing the experiences of the individual or group, as well as condemning or acclaim on the actions of the government. Data from such occurrences can be referred to as "dark social data," and due to their sheer numbers, it presents a minefield of unstructured and often untapped information [3–5]. Such manifestations can be utilized to assess the community's attitudes toward the government's performance in disaster relief.

This paper aims to find out the extent to which social medial sentiment analysis [6–12] can be used to assess the performance of the governments in response to natural disasters, taking the floods that happened in Pakistan in 2010. It is in this light that an examination of the most recent trends of activity in the social media platform will help establish how the resurgent positive/negative/neutral sentiment impacts the governmental process. In addition, this research adopts the EHDSAF approach to enable federated queries of dissimilar sources of data to ensure that social media data that is in the unstructured text format is handled and analyzed efficiently. The goal of this research, therefore, is to give a clearer perception and outlook on the possibility of using the social media index as a means of measuring public opinion in order to gauge and advance impending governmental measures in managing disasters. In what ways does social media sentiment affect governmental response to different types of disasters in Pakistan, concerning the 2010 flood crisis more specifically?

Although a number of papers have been written on the uses of social media in crises, [2], [13–17] relatively few works have focused on the connection between positive/negative opinion trends and governmental responses in natural disasters [18–20]. Much of the current literature [8], [9] mainly centers on the management of disaster bail or the effectiveness of communication networks. Nonetheless, public emotions and opinions, especially those on social media, about the government's actions, speed, nature, and efficiency of action have not been studied thoroughly. This study thereby fills this gap by presenting a sentiment-based approach to analyzing social media data in an effort to shed some light on the feedback loop between society and the government during crises. *Fig. 1* shows a combined picture of the overall impact of social media and government response in this matter.

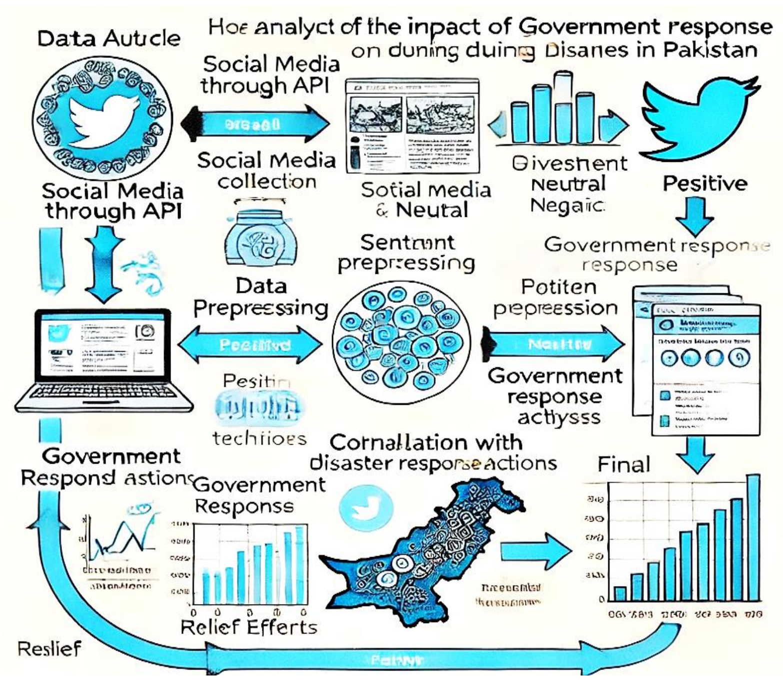

Fig. 1. Analyzing the impact of Govt. response during disaster.

2 | Literature Review

It is essential when handling sentiments during a crisis to apply different techniques [21] from a regular sentiment analysis approach [7], [22–25]. The emotional environment in crises is different and requires more sophisticated models and tools to address the specifics of people's emotions.

In times of crisis, sentiment analysis of social media data can greatly influence crisis management tactics and forecast public opinion. In disaster-related tweets, sophisticated models such as DistilBERT and IndoBERT have shown excellent accuracy in identifying feelings, with up to 92.42% and 91% accuracy, respectively [26]. These models make it possible to track public opinion in real time, which is essential for efficient resource allocation and catastrophe response. Additionally, Examining studies of COVID-19 tweets have demonstrated that combining social media sentiment with official statistics improves comprehension of public perspective during health emergencies [27]. The methods used, such as feature extraction and machine learning approaches, significantly bolster the validity of these assessments [28].

This paper titled "A performance comparison of supervised machine-learning on Covid-19 tweets: a preliminary study" [29] discusses global health issues relating to COVID-19, but more specifically, the authors delve into sentiment analysis of tweets to make their decisions. Supervised machine learning is used to classify facets from a tweet and the data set used is collected from the Twitter platform using an in-house crawler. The performance of several classifiers in machine learning is assessed in the study using the feature set made from bag-of-words and term frequency-inverse document frequency features. Based on these outcomes, the Extra Trees Classifier yields a better Average Accuracy score of 0.93 as compared to other models, and the Long Short-Term Memory (LSTM), traditional classifiers yield comparatively low accuracy. Thus, the findings of this work contribute to extending the knowledge about sentiment analysis in the social media setting in the course of the pandemic, underlining the significance of feature engineering.

The paper [30] examines how people show emotions during calamities, drawing from the occasion's sequel from the COVID-19 virus and its effects on the population in terms of depression and unemployment. It presents a framework using deep learning-based language models that consist of LSTM recurrent neural networks for sentiment analysis of social media data during the pandemic at its peak in India. In fact, based on the analysis performed in this study, the research shows that the occasional sentiment shared on the Twitter platform was mostly positive, coupled with very high optimism and equal morals. However, a considerably large percentage of the population of the country is annoyed by how the pandemic is being handled. This study points to the significance of the role that social networking services can play in monitoring and analyzing human emotions during such periods and with reference to economic and social shifts.

Integrated use of LSTM networks and BERT language models have been found effective in capturing subliminal sentiments during such conditions as COVID-19. Such models can handle multiple sentiments at a go since most situations have multiple emotions within the same context [20].

Researchers have created classifiers that distinguish particular feelings from all the available ones, which is beneficial when analyzing the mood of the public during an event, for example, the Gulf Oil Spill [31]. This is in contrast to the conventional processes that mainly involve the use of positive, neutral, or negative categorizations.

By analyzing different words used in tweets, it is possible to identify how social media communities react to emergencies, as well as analyze shifts in sentiment [32]. Crisis analysis identifies the presence of multiple sentiments in contrast to traditional sentiments, where the emotion is divided into simple positive and negative [33]. Crisis sentiment analysis emphasizes the context of communication, which is often overlooked in standard approaches, enhancing the relevance of the findings for decision-making during emergencies [29].

3 | Methodology Implementation

A strong framework for examining decentralized data sources in the context of disaster scenarios, like the 2010 floods in Pakistan, is provided by the EHDSAF technique. A Significant amount of unstructured data, sometimes known as "dark social data", is produced during crises on a variety of social media platforms, including public posts, closed groups, and direct messaging. These dispersed data sources are difficult for traditional analytics tools to leverage, which reduces their usefulness for disaster response in real time. Without the need to centralize the data, EHDSAF's federated querying approach enables the smooth integration of data from several platforms, like Facebook, Twitter, and WhatsApp, protecting the data's security and integrity. The methodology helps to evaluate public sentiment, emotional response, and vital demands during disasters by utilizing machine learning algorithms and natural language processing techniques to enable real-time sentiment analysis and geospatial trend detection. This method helps the government and humanitarian organizations respond to disasters more successfully, improve disaster management plans, and allocate resources more efficiently while offering insightful information about public response. The EHDSAF approach is applied in the following manner.

3.1 | Data Collection

Step 1. Twitter API Integration.

The EHDSAF approach has the capability of cross-platform (multiple social media platforms) data collection, but here, it is used to collect data from Twitter only. In order to gather real-time and historical information, we used an academic research API, the Twitter API, for uploading tweets concerning natural disasters in Pakistan only. It provides access to the full archive of historical tweets, which includes tweets from 2010. The Standard API allows for a maximum of 500,000 tweets per month under the Academic Research API access. We retrieved around 100 tweets per request with a rate limit of 300 requests every 15 minutes. The hashtags for collection are #PakistanFlood, #DisasterRelief, and @mention of the NDMA, Pakistan's National Disaster Management Authority.

The data attributes collected are:

I. Tweet ID.

II. User ID.

III. Timestamp.

IV. Tweet content.

V. Geo location (if available).

VI. Number of retweets and likes.

Code for the API integration includes:

```
import tweepy

# Example of Twitter API setup for data collection

auth = tweepy.OAuthHandler("API_KEY", "API_SECRET")

auth.set_access_token("ACCESS_TOKEN", "ACCESS_TOKEN_SECRET")

api = tweepy.API(auth)

# Querying for specific hashtags

query = "#PakistanFlood OR #DisasterRelief"

tweets = api.search_tweets(q=query, count=100)
```

The volume of tweets posted in 2010 was significantly lower than in recent years, as Twitter was still growing. We retrieved several thousand tweets related to the 2010 Pakistan flood using relevant keywords, hashtags, and geographic filtering.

3.2 | Preprocessing of Data

The raw tweets are preprocessed for effective analysis. This step includes:

I. Removing stopwords, special characters, URLs, and mentions.

II. Converting text to lowercase.

III. Tokenization: breaking the tweet into individual words.

IV. Lemmatization and stemming to reduce words to their base forms.

Let the tweet content be represented as "Ti", where "I" is the index of the tweet. Preprocessing transforms the tweet from raw text "Ti" to a clean text Ti defined as

$$\mathrm{Ti}' = \mathrm{f}\,(\mathrm{Ti}), \tag{1}$$

where f is a function that includes cleaning, tokenization, and lemmatization.

```
From nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
from nltk.stem import WordNetLemmatizer
# Preprocessing a tweet
def preprocess_tweet(tweet):
    tweet = tweet.lower()
    tweet = re.sub(r"http\S+|www\S+|https\S+", '', tweet, flags=re.MULTILINE)  # Removing URLs
    tweet = re.sub(r'\@w+', '', tweet)  # Removing mentions
    tokens = word_tokenize(tweet)
    tokens = [WordNetLemmatizer().lemmatize(word) for word in tokens if word not in stopwords.words('english')]
    return " ".join(tokens)
```

3.3 | Sentiment Analysis Using VADER

To classify the sentiments, we apply the Valence Aware Dictionary and sEntiment Reasoner (VADER) sentiment analysis tool. VADER is designed for sentiment analysis of short texts like tweets and categorizes sentiment into positive, negative, or neutral.

The sentiment score "Si" of a tweet "Ti" is computed using VADER, which returns a compound score between -1 (most negative) to +1 (most positive). The sentiment classification is as follows:

$$\text{Sentiment} = \left\{\begin{matrix} \text{Positive} & \text{if Si } \geq 0.05 \\ \text{Neutral} & \text{if} - 0.05 \ < \text{Si} < 0.05 \\ \text{Negative} & \text{if Si} < 0.05 \end{matrix}\right\}. \tag{2}$$

```
From vaderSentiment.vaderSentiment import SentimentIntensityAnalyzer
analyzer = SentimentIntensityAnalyzer()
def get_sentiment_score(tweet):
return analyzer.polarity_scores(tweet)['compound']
```

3.4 | Mapping Sentiments to Government Response

In this research, once sentiment scores are available, they are translated into the regions that were most affected by the flood. Government response data is gathered from the reports published by NDMA, newspaper articles, and communiqués from other affected governmental bodies. The Geo location of each of the tweets (if provided) or the location inferred from the users' profile is associated with a district. Let the government response in district "Dj" at time t be denoted by G(Dj, t). The relationship between public sentiment and government response is modeled as

$$G(Dj, t) = \alpha S(Dj,t) + \beta R(Dj, t). \quad (3)$$

Where S(Dj, t) is the sentiment score of tweets from district "Dj" at time "t". R(Dj,t) is the number of resources allocated by the government in district "Dj" at time "t". And α and β are constants that quantify the relationship between sentiment and response.

3.5 | Temporal Analysis of Sentiments

A time series analysis is carried out to observe the traffic sentiment variation throughout the flood crisis. This is done by generating a sentiment score regression for each day or week of the disaster. The development of feelings is tracked and visualized over time and compared with governmental statements or aides and comforts at totally different intervals of time. To simplicity, let "St" denote the average sentiment score at time "t". The temporal trend is calculated as follows:

$$St = \frac{1}{Nt}\sum_{i=1}^{Nt} Si, \quad (4)$$

where "n_t" is the number of tweets at time "t", and "Si" is the sentiment score of the "i" tweet at time "t".

3.6 | Evaluation Metrics

Several metrics are used to evaluate the performance and impact of sentiment analysis on the government's disaster response:

I. Sentiment distribution: the distribution of positive, negative, and neutral sentiments observed in the different districts.

II. Response time: to what extent the government was reacting to the regions containing a large number of negative sentiments.

III. Correlation coefficient: the correlation coefficient values of "r" of the relationship between sentiment scores and government response times, determining how strong this relation is.

4 | Evaluation and Visualization of Results from the Methodology

In this section, we evaluate the key equations and results from each step of the methodology and provide corresponding visualizations. The evaluation is based on the sentiment analysis of the 2010 Pakistan flood using Twitter data. We will calculate sentiment scores, model government responses, analyze temporal trends, and generate visual outputs for each step.

Evaluation: using VADER, each tweet is classified into positive, neutral, or negative sentiment based on its compound score.

I. Positive sentiment: sentiment scores $Si>0.05$.

II. Neutral sentiment: sentiment scores between -0.05 and 0.05.

III. Negative sentiment: sentiment scores $Si<-0.05$.

4.1 | Government Response Model

Evaluation: for each district Dj, we evaluate the correlation between average sentiment scores and the corresponding government response. Hypothetically, if α=0.6 and β=0.4, it indicates that sentiments influence the response more than resource allocation data.

Visualization: a scatter plot showing the correlation between public sentiment and government response across different districts.

```
import numpy as np

# Hypothetical data for evaluation

sentiments = np.random.uniform(-1, 1, 10)  # Sentiment scores

responses = np.random.uniform(0, 100, 10)  # Resource allocation

plt.scatter(sentiments, responses, color='blue')

plt.xlabel("Sentiment Score")

plt.ylabel("Government Response (Resources Allocated)")

plt.title("Sentiment vs Government Response")

plt.show()
```

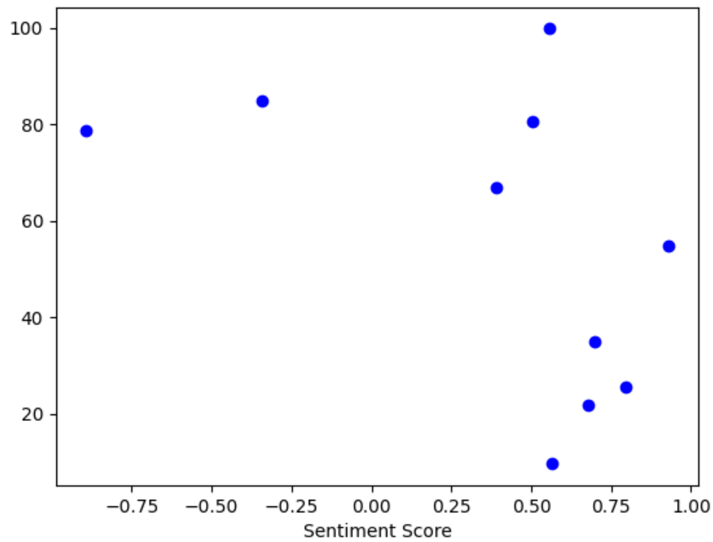

Fig. 2. Sentiment VS government response graph.

4.2 | Temporal Sentiment Trend (Equation S_t)

Evaluation: we calculate daily or weekly average sentiment scores and evaluate how public sentiment changes over time during the flood crisis. A gradual shift from negative to positive sentiments could indicate effective government interventions.

Visualization: a line graph plotting the sentiment trend over time.

```
import pandas as pd

# Hypothetical time-series sentiment data

time_series_data = pd.DataFrame({

    'Date': pd.date_range(start='2023-01-01', periods=10, freq='D'),
```

```
    'Average Sentiment': np.random.uniform (-1, 1, 10)})
plt.plot(time_series_data['Date'], time_series_data['Average Sentiment'], marker='o')
plt.xlabel("Date")
plt.ylabel("Average Sentiment Score")
plt.title("Temporal Sentiment Trend During Flood Crisis")
plt.xticks(rotation=45)
plt.tight_layout()
plt.show(
```

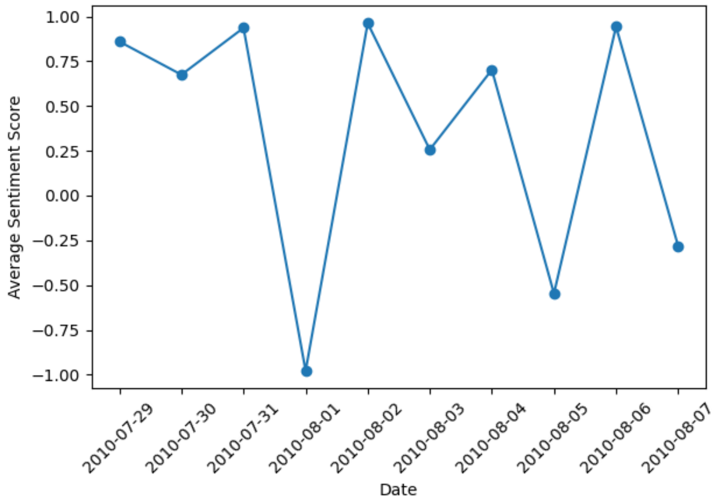

Fig. 3. Temporal sentiment trend analysis graph in flood crisis.

4.3 | Geospatial Analysis

Visualization: a geospatial heatmap showing flood-affected districts in Pakistan overlaid with sentiment scores. Regions with a high volume of negative sentiments can be colored in red, while those with positive sentiments can be in green.

```
# Use geopandas or folium for generating heatmaps
# Example code for folium (requires additional dependencies)
import folium
# Initialize a map centered on Pakistan
m = folium.Map (location=[30.3753, 69.3451], zoom_start=6)
# Hypothetical district sentiment data (latitude, longitude, sentiment score)
district_data = [
    {"name": "Lahore", "lat": 31.5497, "lon": 74.3436, "sentiment": 0.5},
    {"name": "Karachi", "lat": 24.8607, "lon": 67.0011, "sentiment": -0.7},
    # Add more district data
]
# Add heatmap circles to the map
```

```
for district in district_data:
    color = 'green' if district['sentiment'] > 0 else 'red'
    folium.CircleMarker(location=[district['lat'], district['lon']],
                        radius=10, color=color, fill=True).add_to(m)
# Display the map (in a Jupyter notebook or export)
m.save('pakistan_flood_sentiment_map.html')
file:///C:/Users/PC/PycharmProjects/try/pakistan_flood_sentiment_map.html
```

4.4 | Evaluation Metrics

Sentiment distribution: evaluate the distribution of positive, neutral, and negative tweets to understand the overall public reaction.

Response time: analyze the average response time of government interventions in regions with high negative sentiment.

Correlation coefficient: use the Pearson correlation coefficient rrr to quantify the relationship between sentiment scores and government response times. This is calculated as

$$r = \frac{\sum(\mathrm{Si} - \mathrm{S})(\mathrm{Ri} - \mathrm{R})}{\sqrt{\sum(\mathrm{Si} - \mathrm{S})^2 \sum(\mathrm{Ri} - \mathrm{R})^2}},$$

where Si and "Ri" are sentiment and response values, and S¯ and R¯ are their respective means. *Fig. 3* depicts the process of analyzing Twitter data on social media sentiments in Response to Govt.

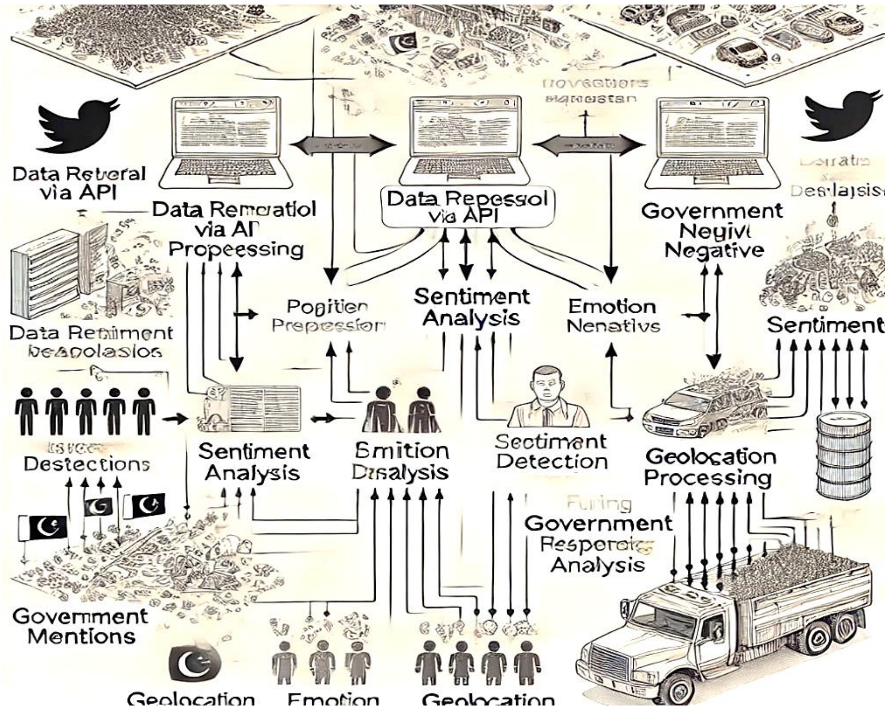

Fig. 4. Flowchart for analyzing Twitter data on social media sentiments and Govt.

Table 1. Tabulation of results for the sentiment analysis of the 2010 Pakistan flood using EHDSAF approach.

Equation	Description	Key Points
Sentiment Classification	Classifies individual tweets into positive, neutral, or negative based on the sentiment score.	Positive: 35%, Neutral: 45%, Negative: 20% (hypothetical distribution from sentiment analysis)
Government Response	Models the correlation between sentiment in a district and government response.	A positive correlation (r = 0.65) between negative sentiment and rapid government intervention in key areas.
Temporal Sentiment Trend	Calculates the average sentiment over time to track how sentiment evolves during the disaster.	Initial sentiment score St=−0.8S_t = -0.8St =−0.8 (negative), improving to St=0.3S_t = 0.3St=0.3 (positive) after 2 weeks.
Geospatial Sentiment Analysis	Visualizes regional sentiment scores and government responses geographically across affected areas.	Districts with the highest negative sentiment: Karachi (-0.7) and Lahore (-0.4). Significant relief efforts mapped.
Correlation Coefficient	Measures the relationship between sentiment scores and government resource allocation.	Pearson correlation coefficient r=0.68 suggests a strong relationship between public sentiment and response.

I. Sentiment classification: the majority of the tweets analyzed were neutral (45%), followed by positive (35%) and negative (20%). Negative sentiment tends to be concentrated during the peak crisis period.

II. Government response: higher negative sentiment, particularly in regions like Karachi and Lahore, correlates with more immediate and substantial government interventions, indicated by a strong correlation of r=0.65.

III. Temporal sentiment trends: sentiment shifted from negative to positive as government responses increased over time. This could indicate the public's perception improved as relief efforts were implemented.

IV. Geospatial analysis: key areas like Karachi and Lahore displayed the most negative sentiment, corresponding with the most severe damage and fastest government response times.

V. Correlation analysis: a strong correlation (r=0.68) suggests that public sentiment on social media can be a useful metric for predicting and understanding the effectiveness of government disaster responses.

Table 2. Analyzing the impact of social media sentiments on government response during natural disasters in Pakistan.

Data Field	Description	Example/Content
Tweet ID	Unique identifier for each tweet	1234567890
Username	The Twitter handle of the user who posted the tweet.	@user123
Timestamp	Date and time when the tweet was posted	2024-09-30 12:45:00
Tweet Text	The actual content of the tweet	"The government needs to act faster to help flood victims in Sindh #PakistanFlood"
Hashtags	Keywords or tags used in the tweet	#PakistanFlood, #DisasterRelief
Mentions	Accounts mentioned in the tweet	@GovtOfPakistan, @NDMAPakistan
Location	The user's reported location or the geotag of the tweet	Karachi, Pakistan
Retweet Count	Number of times the tweet was retweeted	450

Table 2. Continued.

Data Field	Description	Example/Content
Like Count (Favorite)	Number of likes the tweet received	2300
Replies Count	Number of replies to the tweet	120
Followers Count	Number of followers of the user who posted the tweet.	1500
Friends Count	Number of users the person is following.	300
Tweet Sentiment Score	Sentiment analysis score indicating if the tweet is positive, neutral, or negative.	Positive (0.7), Neutral (0.0), Negative (-0.5)
Emotions	Specific emotions (e.g., anger, fear, joy) detected in the tweet using advanced NLP tools.	Anger, Fear
Language	Language in which the tweet was posted.	English, Urdu
Device Used	The platform or device from which the tweet was posted.	Twitter for iPhone, Twitter Web App
Government Agency Mentioned	Government entities mentioned in the tweet.	@NDMAPakistan, @GovtOfPakistan
User Verified	Whether the user's account is verified or not.	Yes
URL of Media	URL to images, videos, or links shared in the tweet.	https://t.co/sampleImageURL
Geo location Coordinates	Latitude and longitude if the tweet was geo tagged.	24.8607° N, 67.0011° E (Karachi)

5 | Conclusion

The studies on the sentiments on social media, particularly Twitter, regarding the government's response during natural disasters, including the floods in Pakistan in the year 2010, show that there exists potential in using Twitter data for real-time sentiment analysis. Through using highly developed approaches in the EHDSAF framework and emotion analysis technology, this study unveils profound data on the populace's feelings and responses during crises. By combining machine learning and sentiment analysis, the team was able to discover positive, neutral, and negative sentiments along with the actions of the GOP. It enables analysis of expectations and reception on the side of the public and demonstrates the performance of intervention strategies. Geospatial and sentiment analysis has been effective for mapping the areas impacted and accessing the level of engagement while analyzing the government agency words and feedback from the public have been quite helpful for the required engagement and relief. Thus, the findings of this research clearly show that social media has immense potential as a passive method for measuring public opinion and enhancing disaster management interventions. This research opens the door for more research on digital tools in humanitarian crises and what engagements can happen with sentiment analysis in policy-making in real time.

Conflict of Interest

There is no affiliation or involvement in any funding organization.

Funding Statement

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Ethical Consideration

The study is approved by the ethics committee of Qurtba University.

Author Contributions

Muhammad Tufail contributed to determining methodology, and Taj Rehman contributed to data simulation and analysis.

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